

# The Detection of Abnormal Breathing Activity by Vision Analysis in Application to Diagnosis of Obstructive Sleep Apnea

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## INTRODUCTION

Obstructive Sleep Apnea is increasingly seen as a common and important condition, contributing to sleep disturbance and consequential daytime sleepiness. This has potentially serious consequences for the individual, employers, and society as a whole. Apnea refers to short spells when breathing stops. In obstructive sleep apnea, the throat constricts during sleep, preventing breathing; the apnea episode often ends with a loud snore and/or gasp. Such an event is sufficient to open the throat muscles to allow breathing, and the patient usually falls asleep again so quickly that the event is not remembered. This cycle repeats itself throughout the night as the muscles relax and the throat blocks again, and the frequency of the episode is used to determine the severity of the syndrome.

A wide range of parameters, including EEG (electroencephalogram) sleep staging, snoring, changes in airway resistance, airflow, and inspiratory effort, as well as oxygen saturation and body movement during “normal sleep” in a Sleep Lab, lead to an understanding of the pathophysiology of sleep apnea (Flemons et al., 2003). According to recent research findings (Bennett, Langford, Stradling & Davies, 1998; Kingshott et al., 2000; Pepperell, Davies & Stradling, 2002), the best predictors of morbidity in individual patients, as assessed by improvements with continuous positive airway pressure therapy (CPAP), are nocturnal oxygen saturation and movement during sleep. Moreover, Siven, Kornecki, and Schonfeld (1996) indicate that the results from traditional polysomnography are highly correlated with the video test results.

Video monitoring has been adopted to assist diagnosis on obstructive sleep apnea. However, video monitoring and interpretation are less well developed, both from a recording and analysis viewpoint, due to the relative computational complexity of video analysis and the significant technical challenges. These include the lighting restriction involved with natural night vision and low illumination, including a lack of no color information; the obscuration of the body by a cover; the variation of human size, shape, and behavior; and the massive volume of video and audio data. The diagnosis of sleep disturbances requires a review of substantial amounts of data (including video footage) by clinicians. There is therefore a need for automated monitoring of human breathing activity to diagnose sleep disorders.

## BACKGROUND

Current breathing monitoring techniques can be categorized into two types: invasive and noninvasive. The invasive approaches include Polysomnography; the Belt (Hyun Medics, 2006) or Strap (Svetlana et al., 2005), which track changes in body circumference during the respiratory cycle; Stick-on Electrodes as a heart-respiratory monitor (David et al., 2005); and Nasal Temperature Probes (Storck, Karlsson, Ask & Loyd, 1996). Published noninvasive techniques include Audio Analysis to monitor tidal volumes from human breathing activity (Amin, Cigada, Fordyce & Camporesi, 1993), Vibration Sensors (David et al., 2003; Randall, 1995), and Thermal Imaging (Murthy, Pavlids & Tsiamyrtzis, 2004; Zhu, Fei & Pavlidis, 2005).

However, these techniques for monitoring breathing activities have various limitations in application to diagnosis of sleep disorders. The obtrusive nature of invasive monitoring equipment can disturb sleep and therefore compromise results. The thermistors used in Polysomnography sense differences in temperature; however, they do not have a linear relationship with true airflow. Consequently, the thermistors may not be sensitive for detecting hypopneas (Flemons et al., 2003). Nasal pressure has a linear approximation of airflow but can produce false-positive events and low quality signals if patients are mouth breathing (Flemons et al., 2003). Regarding strap systems, if the tension on the strap is not calibrated, the system will not track the respiration motion correctly, so adjustment may be necessary. Moreover, measurements on patients with shallow and abdominal breathing patterns may fail because the sensor cannot track adequately in a reproducible manner if the chest displacements during normal breathing and breath-hold are not distinctly different. Concerning thermal imaging techniques (Murthy et al., 2004; Zhu et al., 2005), there are position limitations and geometric constraints for targeting faces, which will not be applicable for unpredicted human sleep behavior. As a result, an investigation of methods for monitoring human breathing activity is crucial for diagnosis of sleep disorders.

## METHODS

In this chapter, we develop a nonintrusive monitoring technique without geometric constraints using infrared video information for identifying abnormal breathing activity in application to diagnosis of obstructive sleep apnea. The proposed technique allows patients to sleep on their back or side, with or without facing the camera. The experiments show that the proposed method obtains promising results in recognizing abnormal breathing events and identifying general body movements. Moreover, the experiments also show that the proposed approach is able to recognize events successfully for patients with shallow and abdominal breathing patterns.

## Objectives

The aim of our research is to support the diagnosis of obstructive sleep apnea. Our primary objective is to

detect abnormal breathing episodes based on vision analysis. This also requires us to distinguish breathing movements from other body movements.

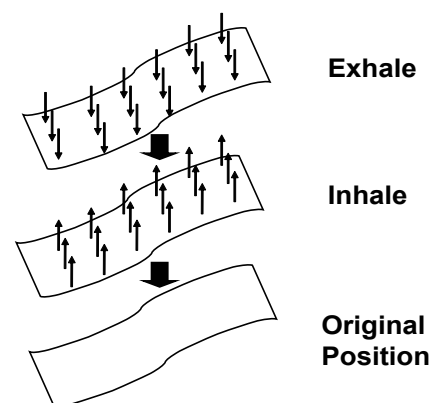
## Technical Analysis in Breathing Behavior

In order to recognize abnormal breathing activities, it is necessary to differentiate between general movements and breathing, allowing further identification of normal breathing status and abnormal breathing status. Thus, we first analyze human breathing behavior in comparison with general body movement and find two important features of the breathing activity. The first is cyclic motion; the elements of the entire surface move forward and backward approximately to their previous position in a breathing cycle (see Figure 1). In contrast, elements tend to move toward different positions for general body movements. Second, considering the rate of movement, breathing is a relatively *slow-motion* activity, compared with other body movements. Hence, in order to detect breathing activity, it is necessary to observe differences across several seconds of video.

## Design

Following the previous analysis, we attempt to distinguish breathing from general body movements based on variations in movements. As the breathing activity is relatively slow, we use an adaptive background model to identify motion; this allows relatively subtle motion to be detected and accumulated within a period of time.

Figure 1. Cyclic moving flow in a breath



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